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1 Introduction

Where are children in single-mother households spatially clustered? Many countries have witnessed an increase in the number of children living in single-mother households. In Japan, the number of single-mother households increased from 867 thousand in 2000 to 1.082 million in 2010 (SBJ, 2017), with a notable 25% increase during this 10-year duration.[5] Children in single-mother households are under high risks of poverty (OECD, 2011, 2018b). The alleviation of child poverty is a crucial policy concern worldwide (Thevenon, 2018; Duncan and Menestrel, 2019). Despite the extensive literature on concentrated neighborhood poverty among disadvantaged families (e.g., Wilson, 1987; Massey and Denton, 1993; Jagowsky, 1997; Sampson, 2012; Allard, 2017), the spatial clustering patterns of children in single-mother households have not been well documented nor have their temporal trends been well examined.

A large body of literature has addressed issues surrounding the spatial inequality among children in disadvantaged families. Prior work suggests that living in impoverished neighborhoods adversely affects socioeconomic outcomes for children (Wilson, 1987; Brooks-Gunn and Duncan, 1997; Cutler and Glaeser, 1997). Although earlier evidence on the neighborhood effects among families that move is mixed (Katz, et al., 2001; Oreopoulos, 2003; Ludwig et al., 2013), recent evidence demonstrates that moving from disadvantaged neighborhoods to better ones creates long-term socioeconomic benefits for children (Chetty, Hendren, and Katz, 2016; Chetty and Hendren, 2018a, 2018b; Chyn, 2018). As suggested by these studies, where one lives matters in the well-being of children. Single-mother households tend to be concentrated in certain areas—often in low-income neighborhoods (Winchester, 1990; Jargowsky, 1997; Rowlingson and McKay, 2002). Nonetheless, our knowledge about the spatial clustering patterns of children in single-mother households is limited.

The purpose of this paper is to shed new light on the spatial inequality by examining the spatial clustering patterns of children in single-mother households. Specifically, we ask the following three questions: (1) Are children in single-mother households spatially clustered in particular regions? (2) Has the spatial clustering intensified or lessened as the number of single-mother households increased? (3) Are the cross-sectional and temporal differences in the proportions of children in single-mother households explained by regional characteristics?

We examine these questions in Japan, where the risk of poverty among children in single-mother households is extremely high. Our analysis employs spatial statistics and spatial panel data models, by using panel data at the municipal level in 2000 and 2010. The panel covers the two periods that are 10 years apart, since comparable data are available only for 2000 and 2010. Single-mother households in our data exclude households with members other than mothers and

[5] The figures are from the Census of Japan (SBJ, 2017). These numbers include households where the mother and children reside with other household members such as grandparents.

children (e.g., grandparents).

Our contributions to the literature are three-folds. First, we examine spatial clustering patterns of children in single-mother households at the municipal level in Japan, for two age ranges of children (younger than 6 and younger than 18). Such an analysis of small geographical units is rare in the literature. In Japan, a majority of single mothers become single when their youngest children are under 6 years old (MHLW, 2017a). Among single-mother households, the poverty rate is higher when children are in the younger age groups than in the older age groups (Tamiya, 2019). The spatial and time constraints, especially for single parents, are severe when children are very young. Thus, the spatial clustering patterns may differ by the ages of the children.

Second, we employ spatial statistics and spatial econometrics that take into account spatial dependency. Our municipal-level data are spatially continuous. The characteristics of neighboring municipalities are unlikely to be mutually independent. Neighboring municipalities may have similarly high proportions of children in single-mother households, forming a spatial clustering of those children. The proportion of children in single-mother households in a municipality may depend not only on the characteristics of that municipality but also on those in neighboring municipalities, with near dependency greater than distant dependency. With the increasing availability of spatial data, applications of spatial statistics and spatial econometrics have received increasing attention (LeSage and Pace, 2009; Anselin and Rey, 2014; Elhorst, 2014; Fageda and Olivieri 2019; Naranpanawa et al., 2019). However, we are unaware of any extant study that applies spatial econometrics to examine the spatial patterns of children in single-mother households. In this study, we use spatial statistics (Global and Local Moran's I) to examine the spatial clustering patterns of children in single-mother households, and employ spatial panel data models (as well as non-spatial panel data models for comparison) to investigate associations between the proportion of children in single-mother households and regional characteristics.

For the regional characteristics, we use the local income, divorce rate, out-migration rate, and availability of childcare centers.[6] Single mothers may choose to live in low-income neighborhoods because of low housing costs, resulting in high concentrations of children in single-mother households in low-income areas.[7] In Japan, divorce is the primary cause of single-parent households. In 2016, divorce accounts for 79.5% of reasons for single mother status (MHLW, 2017a).[8] We expect the

[6] We also examined the college graduate rate (the number of college graduates divided by the population aged 25-64) as a local educational measure. However, the college graduate rate is highly correlated with local income and mostly insignificant in our fixed-effect models. Therefore, we did not include the college graduate rate in our analysis.
[7] We created panel data on the average residential land price using official land price data available from the National Land Numerical Information download service. However, since the official land prices are based on sample data, a number of municipalities have no locations or few with residential land prices. The residential land prices and local income are highly correlated in our data. Therefore, we use local income (the average annual income per person) instead of the residential land price.
[8] Other reasons include unmarried mothers (8.7%), bereavement (8.0%), abandonment (0.5%),

higher divorce rate to be associated with a higher proportion of children in single-mother households. During our study period, the majority of municipalities in Japan experienced excess out migration (the number of out-migrants exceeding the number of in-migrants). In 2010, those municipalities make up nearly three-fourths (73.9%) of the municipalities in Japan (MIC, 2011).[9] Single-mother households may be less likely to move away from their neighborhoods due to a lack of resources and the need to maintain a consistent living environment and local support (including support from relatives and acquaintances) for their children (Kuzunishi, 2017). An increase in the proportion of the out-migration rate may increase the proportion of children in single-mother households. We investigate the availability of childcare centers, given that single-mother households with young children may choose to live near childcare centers for work purposes. We expect a higher availability of childcare centers to be associated with a higher proportion of children in single-mother households.

Third, we examine not only cross-sectional spatial patterns but also temporal changes in the spatial patterns and associations. This study addresses whether the spatial clustering of children in single-mother households intensified from 2000 to 2010. Japan is suitable for a case study, because the number of single-mother households has increased. The proportion of single-mother households among all households with children increased from 5.8% in 2000 to 7.5% in 2010 in Japan (SBJ, 2017).

Our results show significant spatial clustering of children in single-mother households. The spatial clusters of children in single-mother households are located mostly in Hokkaido and western Japan. The spatial clustering patterns for children under age 6 and 18 are similar, but the intensity of spatial clustering is notably greater for children under age 18. Moreover, from 2000 to 2010, the spatial clustering intensified for children under 18, whereas it weakened for children under 6. The regression results of the spatial fixed-effects model indicate that from 2000 to 2010, the proportions of children (both under 6 and 18) in single-mother households increased in areas with low-income growth, high out-migration, and slow growth in the availability of childcare centers. The spatial fixed-effects models exhibit the presence of significant indirect effects (spillover effects), suggesting the importance of addressing spatial dependency.

This article is organized as follows. Section 2 provides background on children and poverty in single-mother households in Japan. Section 3 describes the study area and data, and Section 4 explains our methods. Section 5 reports empirical results, and Section 6 concludes.

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disappearance (0.4%), other (2.0%), and unknown (0.9%) (MHLW, 2017a).

[9] The prefectures that have the highest proportions of municipalities with positive net migration (the number of in-migrants greater than the number of out-migrants) among people aged 15-64 years are Tokyo (59.0%), Kanagawa (54.5%) and Aichi (43.9%), which are all located in metropolitan areas (MIC, 2011).

2 Background: children and poverty in single-mother households in Japan

Many children in Japan face a high risk of poverty. According to the Comprehensive Survey of Living Conditions (CSLS) by the Ministry of Health, Labour and Welfare (MHLW), in 2012, 16.3% of the children (0-17 years) were living in relative poverty in Japan (MHLW, 2017b). The relative poverty rate declined to 13.9% in 2015, but it is higher than the OECD average of 13.4% (OECD, 2018b).

Those figures are for children in general. Children in single-mother households, in particular, witness saliently high poverty risks. In Japan, the relative poverty rate of children under age 20 in single-parent households was 53.1% in 2012 (Abe, 2019), which equates to more than one out of two children in poverty. This poverty rate decreased from 57.9% in 2004 and declined to 43.6% in 2015 (Abe, 2019), but it is markedly higher than the OECD average poverty rate for single-parent households, 31.6% (OECD, 2018b). Moreover, single-parent households are likely to experience persistent poverty rather than temporal poverty (Ishii and Yamada, 2009). The great majority of single-parent households are single-mother households. According to the 2015 Census of Japan, 90% of single-parent households are single-mother households.[10]

Joblessness is not a major reason for the high poverty rate of single mothers in Japan. The majority of single mothers are working but are the working poor. According to the 2016 Nationwide Survey on Single Parent Household, 81.8% of single mothers are employed (MHLW, 2017a). This employment rate for single mothers is notably higher than the OECD average rate of 64.9% in 2014 or the latest available OECD data (OECD, 2016). Nonetheless, many single mothers in Japan are struggling with poverty. Among OECD countries, Japan has the highest poverty rate for one-worker single-parent households (Watanabe and Sikata, 2018). Using the Employment Status Survey data, Tamiya (2019) shows that in 2007, the poverty rate among single mothers is 66.8% even when they have jobs, whereas the poverty rate among two-parent households in which household heads hold jobs is only 8.1%. The high poverty rate among working single mothers relates partly to the large proportion of non-regular employees. In 2016, 48.4% of working single mothers hold non-regular jobs, while 44.2% hold regular jobs (MHLW, 2017a). The 2015 CSLS data indicate that the average employment income of single-mother households is 2.09 million yen, which is considerably lower than that of total households (3.73 million yen) (MHLW, 2017b). In fact, among OECD countries, Japan exhibits the lowest relative disposable income for individuals in one-worker single-parent households (OECD, 2018a).[11]

The high poverty rate of single-mother households in Japan is partly the result of scant support from former spouses or the children's fathers. Studies find that securing child support from

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[10] Those single-parent households exclude members other than a parent and children. The figure is 85% if the other members (e.g., grandparents) are included.

[11] Relative disposable income is mean disposable (after tax and transfer) equalized income as a proportion of disposable equalized income for individuals in households with two or more adults, a working age head, no children and one worker (OECD, 2018a).

nonresident fathers contributes to a reduction in poverty among single-mother households (Skinner et al., 2007; Bartfeld, 2000; Oishi, 2013). Nonetheless, 76% of the single mothers in Japan do not receive child support payments from their children's fathers (MHLW, 2017a), despite the fact that the majority of divorced fathers have the ability to pay it (Zhou, 2014).

The lack of economic resources adversely affects the socioeconomic well-being of children. Nonoyama-Tarumi (2017) demonstrates that a lack of economic resources explains more than half of the educational disadvantage of children in single-mother households in Japan. The college entrance rate of children in single-parent households is 23.9%, which is considerably lower than the 53.7% for total households (MHLW, 2015). Single mothers, who have to manage both raising children and earning income, face not only economic poverty but also time poverty. Compared to married mothers, single mothers in Japan are more likely to work longer hours and spend less time with their children (Tamiya and Shikata, 2007; Raymo, et al., 2014).

Many single mothers in Japan become single when their children are very young. According to the 2016 Nationwide Survey on Single Parent Household, the average age of the youngest children was 4.4 years old when their mothers became single (MHLW, 2017a). Among single mothers, 38.4% became single when their youngest children were under three years old; 57.9% became single mothers when their youngest children were under six years old (MHLW, 2017a). Single mothers with very young children are likely to be young with insufficient work experience. Infants and toddlers need great care. Not only is raising very young children as a sole parent difficult, but searching for or holding down a stable job is difficult as well when children are infants and toddlers. Without sufficient support, maternal and economic hardships are especially severe for single mothers raising very young children.

Based on such circumstances, the government of Japan enacted the law to promote measures against child poverty in 2013. The general principles of the measures consider children in single-parent households as a group of children who need urgent support, and stress the need for more research on the actual state of child poverty to promote the measures against child poverty (CAO, 2014). In August 2019, a panel of experts on the policy measures against child poverty recognized the widening geographical inequality in the anti-child poverty effort and suggested enhancing local governments' efforts so that the future of children would not differ based on the region of their birth (CAO, 2019). Nonetheless, our knowledge about the areas that need more policy support is limited. By examining the spatial clustering patterns of children in single-mother households, this study helps identify areas that need particular policy attention.

3 The study area and data

The study area is Japan comprised of 47 prefectures (Figure 1). Those prefectures are broadly categorized into the following nine regions: Hokkaido, Tohoku, Kanto, Chubu, Kansai, Chugoku, Shikoku, Kyusyu, and Okinawa. The spatial unit of our analysis is a municipality (*shi* = city; *ku* = ward; *machi* = town; and *mura* = village), which is the smallest spatial unit with relevant available data.

In our analysis of children in single-mother households, we use two measures: (1) the proportion of children under age 6 living in single-mother households and (2) the proportion of children under age 18 living in single-mother households. Measure (1) is calculated as the number of children under age 6 in single-mother households divided by the number of children under age 6 in all households. Similarly, measure (2) is computed as the number of children under age 18 divided by the number of children under age 18 in all households. We derive these statistics from the published population data at the municipal level. The number of children in single mother households are reported for only two age ranges: (1) those less than 6 years old, and (2) those less than 18 years old.

We construct panel data on the two measures at the municipality level. The two measures are derived from the Population Census of Japan in 2000 and 2010. We use the census, since the municipal-level analysis requires a sufficient sample size; available survey data have many municipalities with no observations or only a few. The time for our panel data is limited to two years, 2000 and 2010, since comparable data before 2000 are not available.

Single-mother households in our data are the households that consist of unmarried, widowed, or divorced mothers and their children and do not include other members such as grandparents. In the published municipal-level census data of Japan, the numbers of single-mother households that include members other than mothers and children are available only from 2010. In 2010, the majority (69.9%) of the single-mother households did not include other members such as grandparents (SBJ, 2017). The poverty rate of single-mother households without co-residing grandparents is higher than that of single-mother households with co-residing grandparents (Shirahase and Raymo, 2014; Abe, 2019).[12]

During 2000–2010, geographic boundaries of some municipalities changed due to municipal mergers or divisions. In the case of mergers, we aggregated data before mergers into data after mergers; therefore, the boundaries became those in the latest year, 2010. In the case of divisions, we aggregate data after divisions into data before division; accordingly, the boundaries are the ones in the older year, 2000.[13] As a result, the total number of municipalities in our sample is 1,852. We created the municipal boundaries using administrative district data from the National Land Numerical

[12] In 2015, the poverty rate of single-mother households without co-residing grandparents is 48.3%, whereas that of single-mother households living with grandparents is 39.8% (Abe, 2019). Shirahase and Raymo (2014) show that the poverty rate of single mothers is reduced if they co-reside with parents.

[13] In 2006, *Kamikuishiki-mura* (a municipality in Yamanashi prefecture) was divided into two already existing different municipalities, a rare style of division. For this particular division, we calculated population-weighted data for each divided portion of the municipality, using the population at the level of blocks (*kihontaiku*), a spatial unit smaller than municipalities, and then merged the population-weighted data with the data in the existing municipalities.

Information download service.

We created panel data on the local income, divorce rate, out-migration rate, and availability of childcare centers. As a measure of local income, we use average annual income per person, which we calculate as total taxable annual income divided by the number of taxpayers. The data are from municipality taxation status and others [Shichoson Kazei Joukyoutou no Shirabe] available from the Ministry of Internal Affairs and Communications of Japan. For the divorce rate, we use the refined divorce rate, which is calculated as the number of divorces per 1,000 married women (England and Kunz, 1975).[14] The data on the number of divorces based on the Vital Statistics are from the Nikkei Electronic Economic Databank System (NIKKEI NEEDS), and the data on the number of married women come from the Population Census of Japan. The out-migration rate is calculated as the number of excess out-migration (the number of out-migration subtracted by the number of in-migration) divided by the population. Data on out-migration, in-migration, and the population based on the Basic Resident Register are obtained from the NIKKEI NEEDS. The availability of childcare centers is represented by the ratio of the capacity of licensed childcare centers to the population of preschool-aged children (under 6 years old). The data are from the Survey of Social Welfare Institutions and the Population Census. The childcare centers in our data are licensed childcare centers, which are the major providers of childcare services, offering relatively high quality and affordable childcare.

4 Methods

4.1 Global and Local Moran's I

We use Global and Local Moran's I statistics to examine the spatial clustering patterns of children in single-mother households. Global Morans I (Moran, 1948, 1950; Cliff and Ord, 1973, 1981) is an indicator of global spatial autocorrelation. Moran's I is in essence a cross-product statistic between a variable and its spatial lag, in which the variable is expressed in deviations from the mean. The Global Moran's I value (*I*) is given by:

$$\mathrm{I} = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}(y_i-\bar{y})(y_j-\bar{y})}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \quad , \tag{1}$$

where *n* is the number of spatial units (municipalities) indexed by *i* and *j* ($i \neq j$), *y* is the variable of interest, $\bar{y}$ is the mean of *y*, and $w_{i,j}$ indicates the spatial weight between *i* and *j*. Under the null hypothesis of no spatial autocorrelation (or spatial randomness), the expected value of Moran's I and

[14] We also experimented with the crude divorce rate (the number of divorces per 1,000 population) and divorce-to-marriage ratio (the number of divorces to the number of marriages). We decided to use the refined divorce rate, which is considered most appropriate among the three measures.

the z-score are calculated as follows:

$$E[I] \;=\; \frac{-1}{n-1}, \tag{2}$$

$$z_I = \frac{I-E[I]}{\sqrt{V[I]}}. \tag{3}$$

From Eq. (2), we know that the expected value ($E[I]$) is approximately zero when n is large. In this study, statistical significance is assessed by the pseudo p-value ($p = \frac{R+1}{M+1}$), where R is the number of times the calculated Moran's I value from the spatially random data sets (permuted data sets) is equal to or greater than the observed statistic; M equals the number of permutations (Anselin, 2018). We use 99,999 for the number of permutations. If Moran's I statistic is significant, a Moran's I value greater than $E[I]$ implies spatial clustering (positive spatial autocorrelation, or similar values at neighboring municipalities), whereas a Moran's I value less than $E[I]$ indicates spatial dispersion (negative spatial autocorrelation, or dissimilar values at neighboring municipalities). For the spatial weight matrix, we use the first-order binary contiguity matrix based on the queen criterion, where two spatial units are defined as neighbors when they share a common border or vertex. The contiguity matrix is commonly used for data represented by administrative units that vary in size. We standardize the spatial weight matrix so that each row sums to one. The sum of all the weights ($\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}$) results in the number of spatial units (n).

In this study, we present Moran's I statistics, along with Moran scatter plots (Anselin, 1996, 2018). The Moran scatter plots visualize the original variables on the x-axis, spatially lagged variables on the y-axis, and the slopes of the linear fit that equal Moran's I values. The scatter plots are centered on the mean and comprised four quadrants. The upper-right and lower-left quadrants indicate, respectively, *high-high* and *low-low* spatial autocorrelation (positive spatial autocorrelation). In contrast, the lower-right and upper-left quadrants denote, respectively, *high-low* and *low-high* spatial autocorrelation (negative spatial autocorrelation). Global Moran's I statistics and Moran scatter plots help us detect significant spatial clustering, but they do not identify the locations of significant spatial clustering within the study area (in Japan).

To discern those locations, we use Local Moran's I (Anselin, 1995), an indicator of local spatial autocorrelation. The Local Moran's I value (I_i) is computed for each spatial unit i, as follows:

$$I_i = \frac{y_i-\bar{y}}{S_i^2}\sum_{j=1,j\neq i}^{n} w_{i,j}(y_j-\bar{y}), \tag{4}$$

where

$$S_i^2 = \frac{\sum_{j=1,j\neq i}^{n}(y_j-\bar{y})^2}{n-1}. \tag{5}$$

The expected value and *z*-score of Local Moran's I are computed as:

$$E[I_i] \quad = \quad \frac{-\sum_{j=1,j\neq i}^{n} w_{i,j}}{n-1}, \tag{6}$$

$$z_{I_i} = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}}. \tag{7}$$

As in the case of Global Moran's I, the queen-based first-order binary contiguity matrix is used as the spatial weight. A positive $I_i$value indicates that a spatial unit has its neighboring units with similarly high or low values. In this case, the spatial unit is part of a spatial cluster. A negative I_i value means that a spatial unit has neighboring units with dissimilar values. In this case, the unit is a spatial outlier. As in the case of Global Moran's I, statistical significance is assessed by the pseudo *p*-value, which is calculated for each spatial unit, with 99,999 permutations. Based on the 5% significance level ($p < 0.05$), we classify significant locations into four types of spatial association: *high-high* cluster (a statistically significant spatial cluster of high values), *high-low* outlier (a statistically significant spatial outlier with a high value surrounded by low-values), *low-high* outlier (a statistically significant spatial outlier with a low value surrounded by high values), and *low-low* cluster (a statistically significant spatial cluster of low values). We plot the significant spatial clusters and outliers using geographic information systems (GIS) to examine their spatial patterns and temporal changes.

4.2 Non-spatial and spatial panel data models

We use panel data models to examine the relationships between the proportions of children in single-mother households by the age of the children (dependent variables) and local income, the divorce rates, the out-migration rates, and the availability of childcare centers (explanatory variables). First, we estimate non-spatial fixed-effects models. The fixed-effects models are selected, since some omitted municipal characteristics are likely to be correlated with the explanatory variables. Since all of our explanatory variables are time-variant, their coefficients are identified in the fixed-effects models. For comparison, we estimate standard models with ordinary least squares (OLS) for pooled data and non-spatial random-effects models. For an overview of the fixed-effects and random-effects models, see, for instance, Baltagi (2013) and Wooldridge (2016).

The non-spatial panel data models (for both fixed effects and random effects) are expressed as follows:

$$y_{it} = \alpha + X_{it}\beta + v_i + \epsilon_{it} \;\; (i = 1, \dots, N; \quad t = 1,2, \dots, T), \tag{8}$$

where *i* represents units (municipalities), and *t* indicates time (year). α is a scalar, β is a $k \times 1$ matrix, X_{it}

is a vector of observations for unit i and time t. v_i denotes the unobservable unit-specific error term that is time-invariant. The fixed-effects models are estimated by using the within regression estimator. The random-effects models are estimated by using the generalized least squares (GLS) estimator (producing a matrix-weighted average of the between and within results).

Next, we estimate spatial panel data models, since our municipal-level data are likely to be spatially autocorrelated. Spatially aggregate units commonly have inherent spatial correlation. The proportion of children in single-mother households at a location may depend on the proportions at neighboring locations, and vice versa. The proportions of children in single-mother households may also depend on the characteristics of neighboring locations. For details on spatial panel data models, see Baltagi (2013) and Elhorst (2014), among others.

The spatial panel data models are expressed as:

$$\begin{aligned} y_{nt} &= \lambda \mathrm{W} y_{nt} + X_{nt}\beta + c_n + u_{nt}, \\ u_{nt} &= \rho \mathrm{M} u_{nt} + \mathrm{v}_{nt} \quad (t = 1,2,\ldots,T), \end{aligned} \tag{9}$$

where $y_{nt} = (y_{1t}, y_{2t},\ldots, y_{nt})'$ represents an $n \times 1$ vector of observations for the dependent variable for time t with n number of panels; X_{nt} is an $n \times k$ matrix of regressors (including the spatial lags of the regressors); c_n is an $n \times 1$ vector of panel-level effects; u_{nt} is an $n \times 1$ vector of the spatially lagged error, v_{nt} denotes an $n \times 1$ vector of disturbances and is independent and identically distributed (*i.i.d.*) across panels and time with variance σ^2; and W and M indicate $n \times n$ spatial weight matrices. As such, our spatial models include the spatial lags of the dependent variables, spatially weighted averages of the regressors, and spatially correlated errors.

Similar to non-spatial panel data models, our preferred specification is the fixed-effects model, since some omitted municipal characteristics are likely to be correlated with the regressors. The spatial fixed-effects models are estimated with the quasi-maximum likelihood estimators derived by Lee and Yu (2010a). For comparison, we estimate spatial random-effects models, in which c_n is assumed to be normal *i.i.d.* across panels with mean 0 and variance σ_c^2. The random-effects model requires that the panel-level effects are independent of the observed covariates. The random-effects models are estimated with the maximum likelihood estimators derived by Lee and Yu (2010b).

For the spatial weight matrices (W and M), we use the first-order binary contiguity matrix based on the queen criterion, given that characteristics at neighboring municipalities are likely to be correlated. We experiment with the inverse-distance matrix to investigate whether the results are sensitive to different weights. The spatial weight matrices are row normalized, so that each row sums to one.

In both our non-spatial and spatial panel data models, the dependent variable is the proportion of children in single-mother households by the age of the children. The explanatory variables are the log of average income, or local income (lnINC), the refined divorce rate divided by 100 (RDR/100), the out-migration rate (OMIGR), and the availability of childcare centers (CHILDC). We divide the refined divorce rate (RDR) by 100, since the estimated coefficients are too small with the original RDR. We also include a year dummy (Y2010) and the interactions between the year dummy and the explanatory variables to examine whether the associations between the proportion of children in single-mother households and the explanatory variables changed over time.

For each explanatory variable, we present the average marginal effect for the total period between 2000 and 2010 and each year of 2000 and 2010. In the spatial models, the coefficient estimates do not represent marginal effects, since the coefficient estimates involve feedback effects passing through neighboring municipalities and back to the municipalities. Therefore, the average total, direct, and indirect effects are calculated as the average marginal effects. The total effect is the sum of the direct and indirect effects (or spillover effect). Each sample excludes municipalities with null values or no neighboring municipalities. Our data are balanced panel data. The summary statistics for the variables in our regression are given in Table 1.

5 Results

5.1 Geographic results

Figure 2 depicts the proportions of children in single-mother households by the age of the children in 2000 and 2010 at the municipal level. Municipalities with null values are excluded in each map. The summary statistics are presented alongside each map. The choropleth maps reveal three salient geographic features regarding the children in single-mother households. First, the proportions of children in single-mother households are not spatially uniform. The average proportion of children under age 18 in single-mother households was 5.4% in 2010, but there are municipalities where the value is as low as 0% and as high as 24.6%. Second, the temporal changes in those proportions are also not spatially uniform. While some municipalities exhibit noticeable increases (particularly in Hokkaido and western Japan), others show modest decreases or increases (especially in Tohoku and Chubu regions). Of note, the municipalities with remarkable increases tend to be the municipalities where the proportions are already high in 2000. Finally, there is spatial clustering; municipalities with a high proportion of children in single-mother households tend to be geographically close to each other.

Figure 3 presents the Moran scatter plots of the proportions of children in single-mother households by the age of the children in 2000 and 2010. The corresponding Global Moran’s I statistics are shown in the upper center of each scatter plot. The sample excludes municipalities with null values or no neighboring municipalities (n = 1801). The values in the scatter plots are standardized, and the units in both axes are in standard deviations (the mean is zero and the standard deviation is one). The scatter plots are presented in square shapes, which is recommended when both axes are measured in the same units to avoid data distortion (Anselin, 2018). The Moran scatter plots and statistics exhibit the presence of significant spatial clustering of children in single-mother households. There is a linear relationship between the proportions of children in single-mother households in a municipality and its neighboring municipalities. The slopes of the fitted lines correspond to Moran's I values. Moran's I values are all highly significant, suggesting a strong rejection of the null hypothesis (spatial randomness). Positive Moran's I values indicate that high and low proportions are spatially clustered, supporting the visualized data in Figure 1.

The Moran scatter plots and statistics reveal two notable trends that are not apparent in the choropleth maps in Figure 1. First, the intensity of spatial clustering is greater for children under age 18 than for children under age 6. In 2000, the Moran's I value is 0.499 (z-value = 32.396) for children under age 18, while it is 0.379 (z-value = 24.738) for children under age 6, suggesting that the older children are more spatially clustered. Second, from 2000 to 2010, the spatial clustering intensified for both age groups of children. For children under age 6, the Moran's I value increases from 0.379 (z-value = 24.738) to 0.382 (z-value = 24.967). For children under age 18, the value grows from 0.499 (z-value=32.396) to 0.517 (z-value = 33.754).[15]

Figure 4 shows the Local Moran cluster maps of the proportions of children in single-mother households by the age of the children in 2000 and 2010. Table 2 reports the corresponding numbers of municipalities that are significant spatial clusters and outliers at the 5% significance level. Each map excludes municipalities with null values or no neighboring municipalities (n = 1,801). The cluster maps unveil the presence of a number of spatial clusters and outliers as well as their locations. High-high clusters represent municipalities with a high proportion of children in single-mother households surrounded by municipalities with a similarly high proportion. In both 2000 and 2010, the high-high clusters are located mostly in Hokkaido and western Japan, indicating that children in single-mother households are spatially clustered in those regions. High-low outliers depict municipalities with a high proportion of children in single-mother households surrounded by municipalities with a dissimilarly low proportion. The high-low outliers imply that in these municipalities, children in single-mother households are concentrated in isolated areas. The numbers of high-low outliers are relatively small. Most of the high-low outliers are sparsely located in the main island (Honshu) of Japan.

There are a number of low-low clusters, which depict municipalities with a low proportion surrounded by municipalities with a similarly low proportion. Many low-low clusters are located in the Honshu area, indicating that children in single-mother households are relatively rare in those regions. The numbers of low-high outliers are comparatively small. Notably, low-high outliers are

[15] We also calculated differential Moran's I statistics (Anselin, 2019), or Global Moran's I statistics for the changes in the proportions of children under ages 6 and 18 in single-mother households from 2000 to 2010. The resultant statistics are significant at the 1% level.

located mostly in Hokkaido and western Japan where a number of high-high clusters exist, and many low-high outliers in those regions are geographically close to the high-high clusters.

The spatial patterns of spatial clusters and outliers for children under age 6 and under age 18 are similar. However, the numbers of spatial clusters are notably greater for children under age 18. In 2010, the number of high-high clusters is 154 for children under age 6, whereas it is 230 for children under age 18. Similarly, the number of low-low clusters in 2010 is 209 for children under age 6, whereas it is 294 for children under age 18. The greater numbers of spatial clusters for children under age 18 align with the larger Global Moran's I values and their significance for children under age 18 (Figure 2).

The temporal changes from 2000 to 2010 for children under age 6 and those for children under age 18 show similar spatial patterns. However, the temporal changes in the number of high-high clusters differ by the age of the children. Whereas the number of high-high clusters decreased for children under age 6 (from 166 to 154), it increased for children under age 18 (from 215 to 230). This result suggests that the spatial clustering of children in single-mother households weakened for children under age 6 but rose for children under age 18. The numbers of low-low clusters, on the other hand, increased for both age groups, from 183 to 209 for children under age 6 and from 256 to 294 for children under age 18. Accordingly, the total numbers of high-high and low-low clusters increased for both age groups, from 349 to 363 for children under age 6 and from 471 to 524 for children under age 18. This result is consistent with the finding from the Global Moran's I statistics, which indicate the increased intensity of spatial clustering for both age groups (Figure 2).

For both the children under age 6 and the children under age 18, new high-high clusters tended to appear in areas geographically close to existing high-high clusters in Hokkaido and western Japan. In those areas, the high-high clusters extended during the 10-year period. A noticeable number of new high-high clusters are also found in the Shikoku region, especially in Kochi prefecture (the southern prefecture in the Shikoku region), in which there were a few high-high clusters in 2000.

5.2 Estimation results

Table 3 shows the estimation results for the proportion of children under age 6 in single-mother households, from the non-spatial models (pooled OLS, fixed effects, and random effects) and spatial models (fixed effects and random effects). In both the non-spatial and spatial models, our preferred specifications are the fixed-effects models. The pooled OLS and random-effects models are presented for comparison. In both non-spatial and spatial models, the Hausman's (1978) test statistics are significant, rejecting the random-effects specifications. The Wald test of the spatial terms indicates that the additional spatial terms are jointly significant at the 1% level (whether the model is fixed or random), thereby implying the importance of considering spatial dependency.

Table 4 reports the average marginal effects. The left side shows the average marginal effects of the non-spatial models. We begin by interpreting the results of the non-spatial fixed-effects model unless otherwise noted. The average marginal effects of local income (lnINC), the refined divorce rate (RDR/100), the out-migration rate (OMIGR), and the availability of childcare centers (CHILDC) are all significant. Except for the availability of childcare centers, the signs of the marginal effects are as we expected and consistent with those in the pooled OLS and random-effects models. The values of the average marginal effects indicate that a 1% increase in local income is associated with a 0.024 percentage point decrease in the proportion of children under age 6 in single-mother households. An increase of one divorce per 1,000 married women is associated with a 0.041 percentage point increase in the proportion of those children. A 1% increase in the out-migration rate is associated with a 0.103 percentage point increase in the proportion of those children. The negative marginal effect of the availability of childcare centers contradicts our expectation. The results by year show that this negative marginal effect is significant in 2000 but insignificant in 2010.

The average marginal effects of local income, the divorce rate, and the out-migration rate by year reveal that their magnitude and significance increased from 2000 to 2010. The magnitude of the marginal effect of local income increased from -0.020 to -0.027, that of the refined divorce rate (divided by 100) from 0.017 to 0.066, and that of the out-migration rate from -0.053 to 0.260. In 2010, the marginal effects of local income, the refined divorce rate, and the out-migration rate are all significant and their signs agree with our expectations.

Next, we interpret the results based on the spatial fixed-effects model, unless otherwise noted. The upper part of Table 4 reports the average total, direct, and indirect effects for the period between 2000 and 2010. The total effects of local income, the out-migration rate, and the availability of childcare centers are significant and greater in magnitude than the average marginal effects in the non-spatial fixed-effects model. This result suggests that the effects of these variables are larger when they incorporate both direct and indirect effects (spillover effects). Note that indirect effects are assumed to be zero in the non-spatial models.

For local income, the direct effect is insignificant, whereas the indirect effect is significant. The significant and negative indirect effect indicates that, when local income in neighboring municipalities rises, the proportion of children under age 6 in single-mother households (in their municipality) falls. The insignificant direct effect is difficult to explain, possibly because the income level within a municipality is not uniform. Note that the total effect that incorporates both direct and indirect effects is significant and negative, as expected.

The total effect of the refined divorce rate is insignificant, owing to the insignificant indirect effect. The direct effect is significant and its value is similar to that in the average marginal effect in the non-spatial fixed-effects model.[16] For the out-migration rate, the total, direct, and indirect effects are

[16] The direct effect in the spatial fixed-effects model is 0.00041, and that in the non-spatial fixed-effect model is 0.00047.

all significant, and their signs agree with our expectations. The significant and positive direct and indirect effects suggest that the proportion of children under age 6 in single-mother households increased in this and neighboring municipalities that experienced a high out-migration rate. For the availability of childcare centers, the direct effect is significant, whereas the indirect effect is insignificant. This result suggests that an increase in the proportion of children under age 6 in single-mother households is significantly associated with a decrease in the availability of childcare centers in their municipality but is not significantly associated with that in neighboring municipalities.

The lower part of Table 4 presents the total, direct, and indirect effects that are differentiated by year. One notable change is the out-migration rate. While the total, direct, and indirect effects of the out-migration rate are insignificant in 2000, they become significant and larger in magnitude in 2010. In 2010. the total effect of the out-migration rate (0.608) is noticeably greater than the marginal effect in the non-spatial fixed-effects model (0.260). Given that the direct effect (0.237) has a similar value to the marginal effect in the non-spatial fixed-effects model (0.260), the larger total effect arises from the relatively large indirect effect (0.370). Another noteworthy change is that the availability of childcare centers has significant total and direct effects in 2000, but those effects become insignificant in 2010.

Table 5 reports the estimation results for the proportion of children under age 18 in single-mother households. In all the non-spatial and spatial models, the coefficients on the year dummy (Y2010) are positive and significant, suggesting that the proportion of children under age 18 in single-mother households grew from 2000 to 2010, even after controlling for local income, the refined divorce rate, the out-migration rate, and the availability of childcare centers. The Hausman's test statistics are significant in both the non-spatial and spatial models, rejecting the random-effects specifications. The Wald tests of the spatial terms are highly significant at the 1% level, indicating that the spatial terms are jointly significant.

Table 6 presents the average marginal effects. We begin with our interpretation of the non-spatial fixed-effects model. The marginal effects of local income and the out-migration rate are significant with the expected signs, indicating that a decrease in local income and an increase in the out-migration rate augments the proportion of children under age 18 in single-mother households. This result is consistent with that for the pooled OLS and random-effects models. The marginal effect of the refined divorce rate is insignificant, although it is significant in the pooled OLS and random-effects models. The availability of childcare centers has a negative and significant marginal effect, as in the case of the proportion of children under age 6 in single-mother households (Table 4). The results by year exhibit that the magnitude and significance of the marginal effects of local income, the refined divorce rate, and the out-migration rate rose from 2000 to 2010. The marginal effect of the availability of childcare centers lessened its magnitude but continues to be significant. In 2010, all the marginal effects are significant at the 1% level.

Next, we interpret the results based on the spatial fixed-effects model, unless otherwise noted.

The total effects of local income, the refined divorce rate, the out-migration rate, and the availability of childcare centers are all greater in magnitude than the marginal effects of those variables in the non-spatial fixed-effect model. This result suggests that the marginal effects are greater when the model incorporates both direct and indirect effects (spillover effects).

The total effects of local income, the refined divorce rate, the out-migration rate, and the availability of childcare centers are all significant. The total effect of local income indicates that a 1% increase in local income is associated with a 0.1 percentage point decrease in the proportion of children under age 18 in single-mother households. For local income, the direct effect is insignificant, whereas the indirect effect is significant, as in the case of children under age 6 in single-mother households (Table 4). The total effect of the refined divorce rate is significant and negative. The direct effect, however, is positive and significant. The negative total effect, therefore, comes from the significant and negative indirect effect. This result suggests that an increase in the refined divorce rate in the municipality augments the proportion of children under age 18 in single-mother households, but an increase in the refined divorce rate in neighboring municipalities lessens that proportion.

The significant and positive total effect of the out-migration rate implies that a 1% increase in the out-migration rate is associated with a 0.519 percentage point increase in the proportion of children under age 18 in single-mother households. For the out-migration rate, the direct and indirect effects are both significant with expected positive signs. This result suggests that an increase in the out-migration rate in the municipality as well as in the neighboring municipalities raises the proportion of children under age 18 in single-mother households. The results by year exhibit that from 2000 to 2010, the average total, direct, and indirect effects of the out-migration rate all grew in magnitude and significance, as in the case of the proportion of children under age 6 in single-mother households (Table 4).

We also estimated the same spatial models using the inverse-distance spatial weight matrix. The Hausman's test statistics reject the random-effects specifications, as in the case of the models using the first-order contiguity matrix. Table A1 summarizes the average total, direct, and indirect effects in the spatial fixed-effects models. The signs of the significant variables are the same as those in the models using the first-order contiguity weight. The magnitude of the direct effects is mostly similar between the two different spatial weights. Notable differences appear in the indirect effects and resultant total effects. The indirect effects in the models using the inverse-distance spatial weights are markedly larger in magnitude than those in the models with the first-order contiguity spatial weights. This result occurs since the inverse-distance weights take into account the effects from not only neighboring municipalities but also municipalities farther away, although the weights in those distant municipalities are smaller. Since municipal characteristics are unlikely to be dependent on municipal characteristics in faraway locations, we prefer the contiguity weights to the inverse-distance weights in this study. The use of the same contiguity matrix, however, may distort the true spatial relationships, since the spatial relationships are likely to vary by location. The exploration of the appropriate spatial weights is a topic for future research.

6 Conclusions

Children in single-mother households are not uniformly distributed across municipalities in Japan. As indicated by Global and Local Moran's I statistics, there are significant spatial clusters of high proportions of children in single-mother households (high-high clusters). Those spatial clusters are located mostly in Hokkaido and western Japan. The spatial clustering patterns for children under age 6 and under age 18 are similar, but the intensity of spatial clustering is notably greater for children under age 18, with a larger number of high-high clusters. From 2000 to 2010, the number of single-mother households in Japan increased by 25%. During this 10-year period, the number of high-high clusters increased for children under age 18 but decreased for children under age 6. These results suggest that older children in single-mother households are more residentially clustered, and this trend intensified over the 10-year period.

The total effects in the spatial fixed-effects models indicate that the proportions of children (both under ages 6 and 18) in single-mother households increased in areas with low income growth, high out-migration rate, and slow growth in the availability of childcare centers. The negative effect of local income is in line with the findings that single-mother households are concentrated in low-income neighborhoods (Winchester, 1990; Jargowsky, 1997). The positive effect of the out-migration rate suggests that single-mother households might be less likely to move far away from their neighborhoods. The negative effect of the availability of childcare contradicts our expectation. This result implies that there is a need for a policy that helps single-mother households access childcare centers.

The spatial fixed-effects models exhibited the presence of significant indirect effects (spillover effects). The magnitude of the total effects in the spatial fixed-effects models is greater than that of the marginal effects in the non-spatial fixed-effects models, suggesting the sizable indirect effects. These results point to the importance of addressing spatial dependency.

Our findings imply that policies aimed at helping children in single-mother households should not be uniform across regions. Policy measures to support single-mother households vary by local government. In Japan, since the enactment of the law to promote measures against child poverty in 2013, various efforts have been made to reduce child poverty. Meanwhile, regional inequality in anti-child poverty policy efforts has widened in recent years (CAO, 2019). Affluent municipalities may provide better support, whereas poor municipalities may be unable to provide adequate support. There may be a geographical mismatch between areas that need more support and areas that offer better support. Our results can help identify such geographical mismatch as well as critical areas that need further policy attention.

Due to the availability of data, our panel was short—only two years, 2000 and 2010. However, spatial data are increasingly available. Future research could use spatial panel data that include years after 2010. In this study, we used the same spatial weights for all municipalities. However, spatial relationships are likely to differ by location. The exploration of various spatial weights at different locations is another possibility for further research. Such research using spatial panel data improves our understanding of the spatial inequality among children in disadvantaged families.

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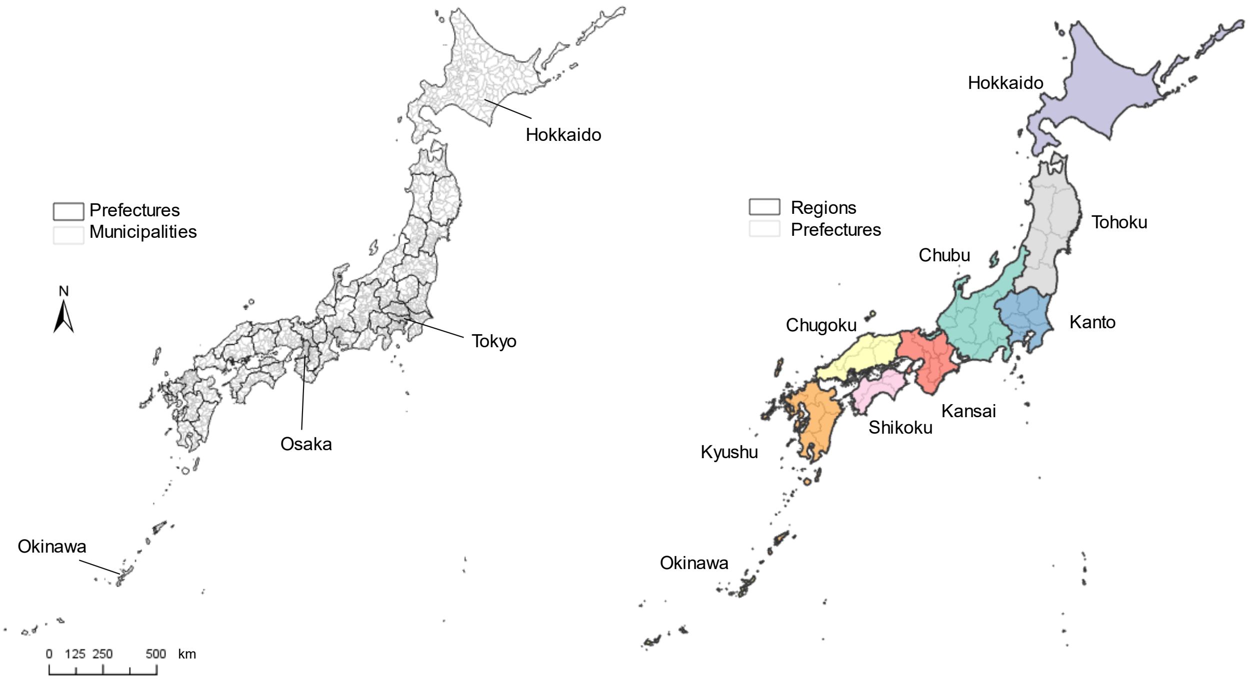
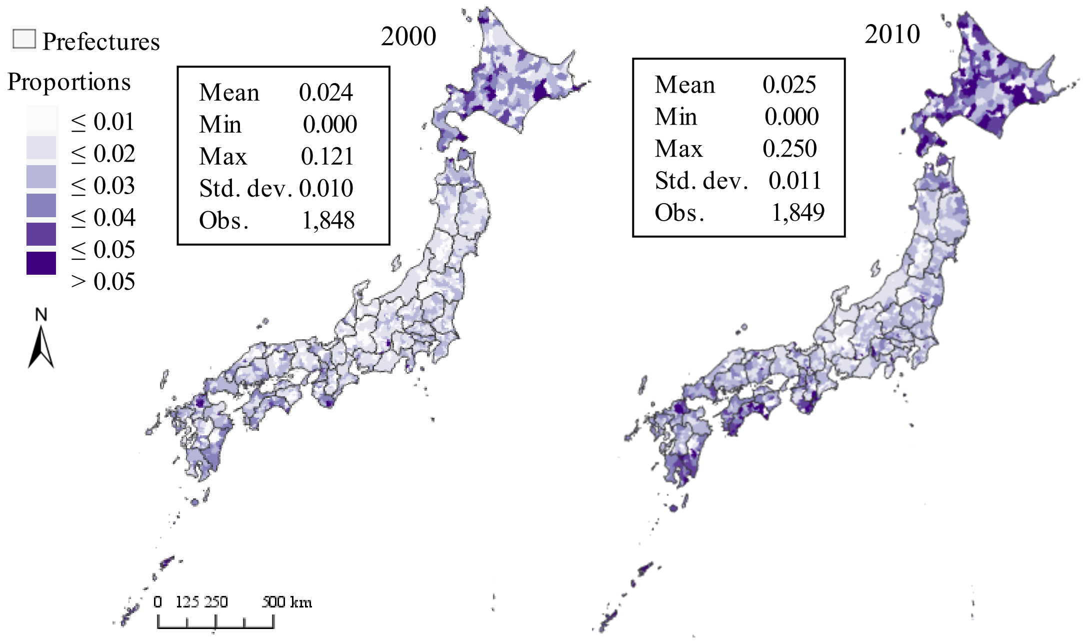


Figure 1 Regions, prefectures, and municipalities of Japan

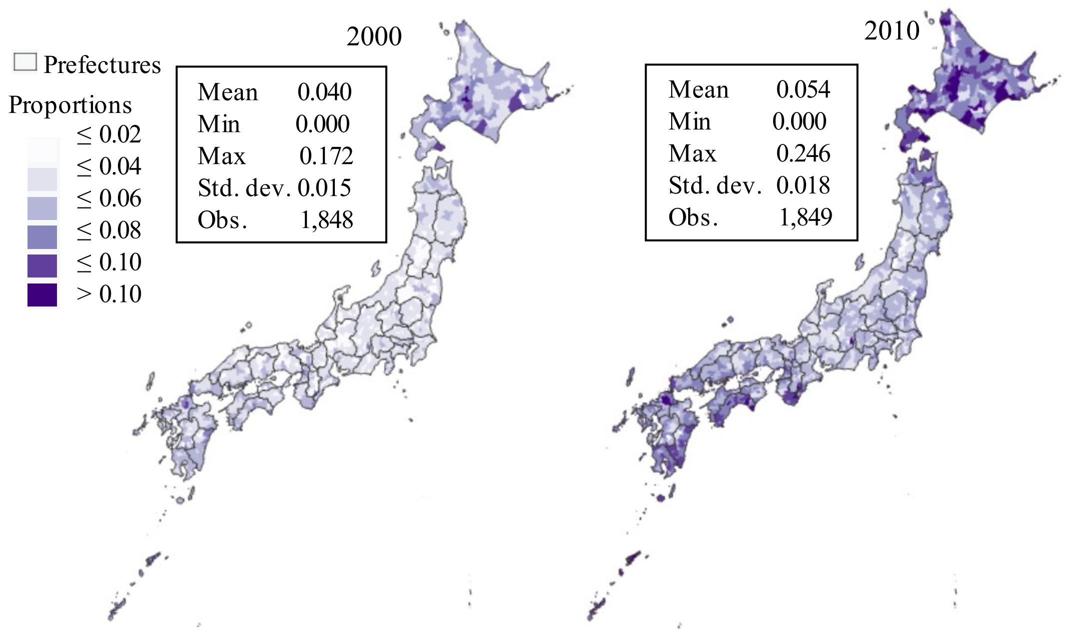
Table 1 Summary statistics

Variable	Pooled (*N* = 3602, *T* = 2) Mean	Std. dev.	Min.	Max.	2000 (*N* = 1801) Mean	Std. dev.	Min.	Max.	2010 (*N* = 1801) Mean	Std. dev.	Min.	Max.
Proportion of children in single-mother households												
Children < 6	0.023	0.015	0.000	0.203	0.020	0.013	0.000	0.121	0.025	0.016	0.000	0.203
Children <18	0.044	0.023	0.000	0.246	0.034	0.018	0.000	0.172	0.053	0.023	0.000	0.246
Log of average income (lnINC)	8.007	0.170	7.563	9.152	8.088	0.142	7.702	8.924	7.925	0.155	7.563	9.152
Refined divorce rate /100 (RDR/100)	0.069	0.026	0.000	0.278	0.069	0.027	0.000	0.246	0.070	0.025	0.000	0.278
Out-migration rate (OMIGR)	0.002	0.007	-0.079	0.068	0.002	0.008	-0.079	0.068	0.002	0.006	-0.039	0.035
Availability of childcare centers (CHILDC)	0.457	0.297	0.000	4.500	0.424	0.260	0.000	2.388	0.490	0.327	0.000	4.500

Note : Each sample excludes municipalities with null values or no neighboring municipalities.



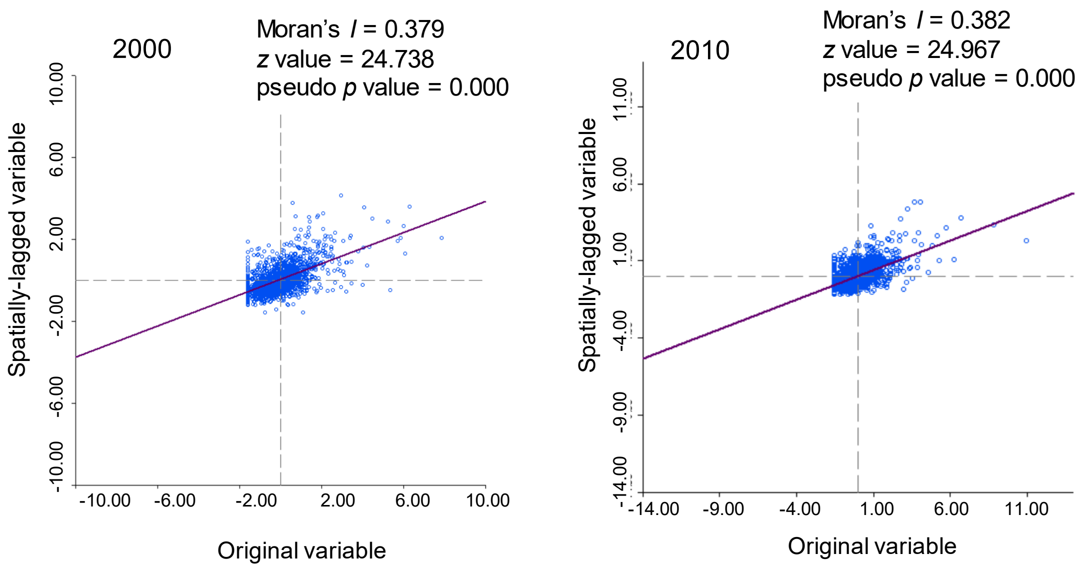
Children under 6 in single-mother households



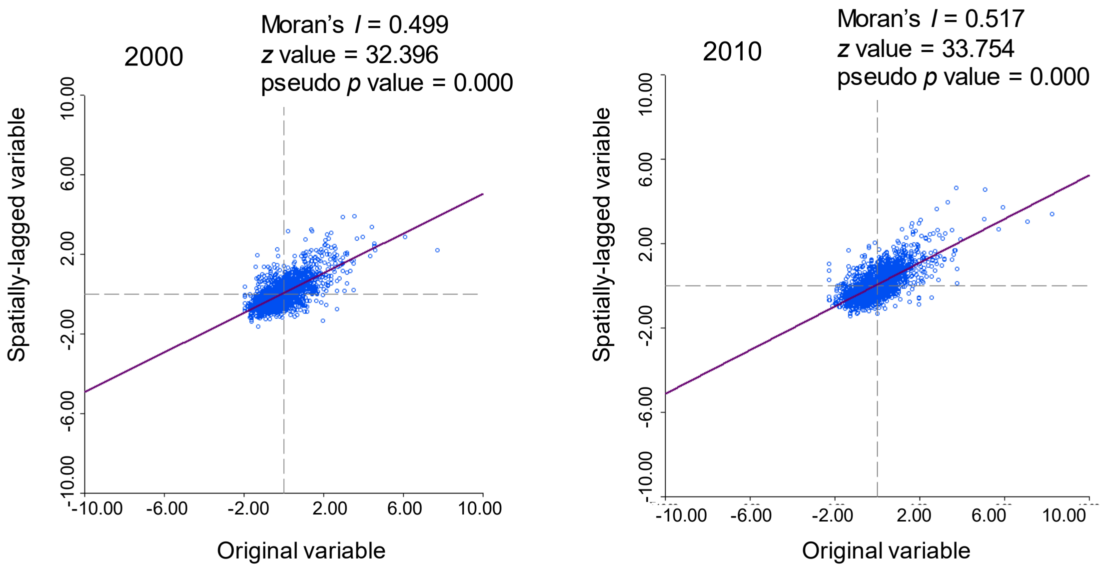
Children under 18 in single-mother households

Note: The proportions in 2000 and 2010 are weighted by the numbers of children under 6 (upper maps) or 18 (lower maps). Municipalities with null values are excluded in each map.

Figure 2 The proportions of children in single-mother households by the age of children

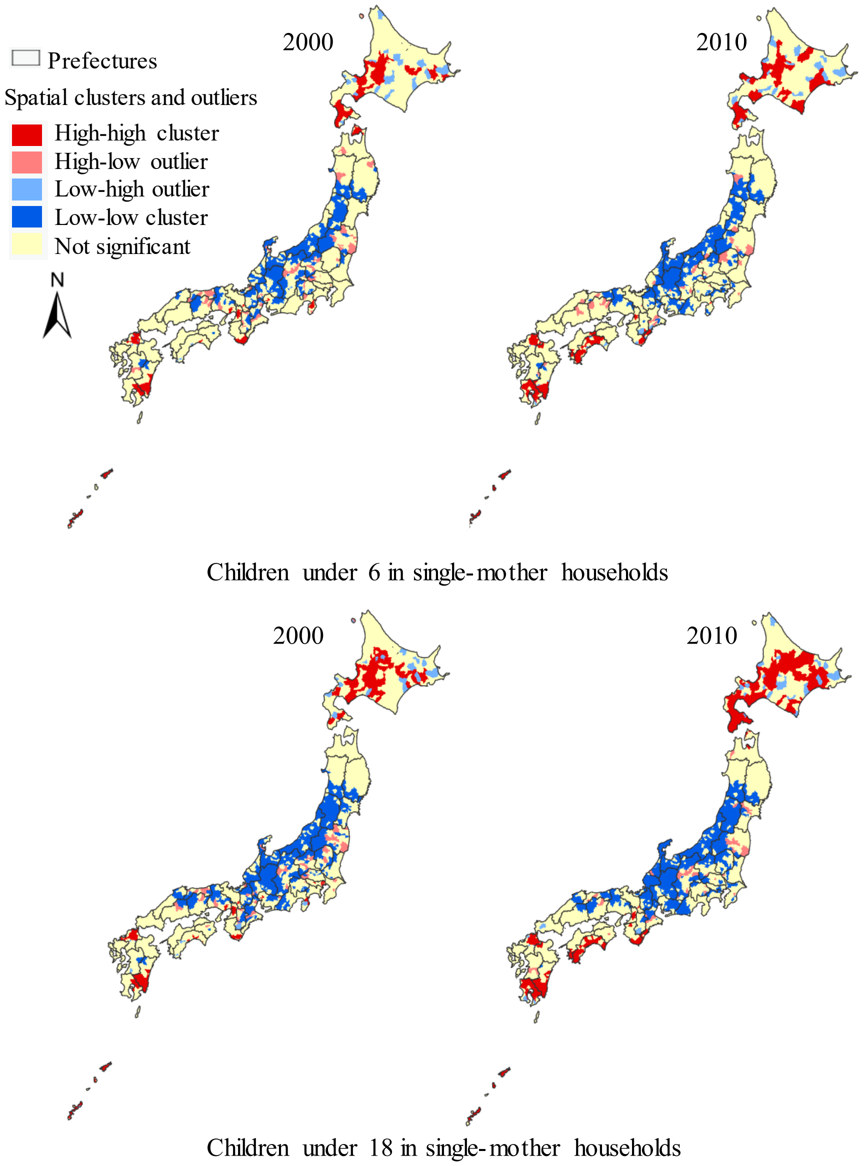


Proportion of children under 6 in single-mother households



Proportion of children under 18 in single-mother households

Figure 3 Moran scatter plots and statistics: the proportions of children in single-mother households by the age of children



Note: Municipalities with null values or no neighboring municipalities are excluded. The total numbers of municipalities is 1,801.

Figure 4 Local Moran cluster maps: the proportions of children in single-mother households by the age of children

Table 2 Local Moran's I: the numbers of spatial clusters and outliers

	High-high clusters	High-low outliers	Low-high outliers	Low-low clusters	Not significant
Proportions of children in single-mother households					
Children under 6					
2000	166	41	27	183	1384
2010	154	29	34	209	1375
Children under 18					
2000	215	38	28	256	1264
2010	230	30	29	294	1218

Note : Each sample excludes municipalities with null values or no neighboring municipalities. The total number of observations (municipalities) in each sample is 1,801.

Table 3 Estimation results of children under age 6 in single-mother households

	Non-spatial models									Spatial models					
	Pooled OLS			Fixed effects			Random effects			Fixed effects[a]			Random effects		
	β	std error		β	std error		β	std error		β	std error		β	std error	
lnINC	-0.013	0.002	***	-0.020	0.006	***	-0.009	0.002	***	-0.003	0.007		-0.007	0.003	**
RDR/100	0.290	0.008	***	0.017	0.016		0.223	0.011	***	0.025	0.015	*	0.160	0.011	***
OMIGR	0.217	0.035	***	-0.053	0.044		0.027	0.038		-0.056	0.044		-0.003	0.035	
CHILDC	0.002	0.002		-0.007	0.002	***	-0.002	0.001		-0.006	0.002	***	-0.004	0.001	***
Y2010	0.115	0.019	***	0.053	0.019	***	0.055	0.020	***	0.009	0.013		0.003	0.012	
lnINC × Y2010	-0.013	0.002	***	-0.007	0.002	***	-0.007	0.002	***	-0.002	0.002		-0.001	0.001	
RDR/100 × Y2010	-0.112	0.011		0.049	0.014	***	0.029	0.014	**	0.048	0.011	***	0.035	0.009	***
OMIGR × Y2010	-0.007	0.061		0.313	0.058	***	0.320	0.056	***	0.267	0.048	***	0.231	0.042	***
CHILDC × Y2010	-0.004	0.002	*	0.006	0.001	***	0.003	0.001	**	0.004	0.001	***	0.002	0.001	***
Constant	0.102	0.014	***	0.185	0.053	***	0.077	0.019	***				0.034	0.014	**
Spatially weighted															
W × lnINC										-0.026	0.010	**	0.003	0.004	
W × RDR/100										-0.044	0.025	*	-0.052	0.015	***
W × OMIGR										0.079	0.068		0.066	0.051	
W × CHILDC										0.000	0.002		0.004	0.001	***
W × dependent variable										0.523	0.047	***	0.674	0.019	***
W × errors										-0.565	0.070	***	-0.703	0.041	***
Standard deviation of panel effects				0.013			0.008						0.006		
Standard deviation of errors				0.009			0.009			0.008			0.008		
ρ				0.683			0.468								
Hausman test							236.79 (p = 0.00)						195.75 (p = 0.00)		
Wald test of spatial terms										167.90 (p = 0.00)			1506.20 (p = 0.00)		

Note : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each sample excludes municipalities with null values or no neighboring municipalities. *W* is the binary contiguity matrix. The total number of observations (all) in each sample is 1,801 (3,602). The pooled OLS is weighted by population. [a] The standard deviation of the panel effects is not presented, since the spatial fixed-effects estimator does not provide consistent estimates for the levels of the panel fixed effects nor for their standard deviation.

Table 4 Average marginal effects for children under age 6 in single-mother households

	Non-spatial models			Spatial models: fixed effects			Spatial models: random effects		
	Pooled OLS	Fixed effects	Rondom effects	Total	Direct	Indirect	Total	Direct	Indirect
2000-2010									
lnINC	-0.019 ***	-0.024 ***	-0.012 ***	-0.062 ***	-0.008	-0.054 ***	-0.014 ***	-0.008 ***	-0.006
	(0.001)	(0.006)	(0.002)	(0.013)	(0.007)	(0.014)	(0.005)	(0.003)	(0.005)
RDR/100	0.236 ***	0.041 ***	0.237 ***	0.011	0.047 ***	-0.036	0.385 ***	0.192 ***	0.193 ***
	(0.006)	(0.014)	(0.009)	(0.044)	(0.014)	(0.042)	(0.032)	(0.010)	(0.030)
OMIGR	0.214 ***	0.103 **	0.187 ***	0.328 ***	0.094 **	0.234 **	0.547 ***	0.144 ***	0.403 ***
	(0.030)	(0.040)	(0.032)	(0.124)	(0.040)	(0.118)	(0.126)	(0.031)	(0.119)
CHILDC	0.000	-0.004 ***	0.000	-0.008 *	-0.004 ***	-0.004	0.004	-0.002 ***	0.006 **
	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.004)	(0.003)	(0.001)	(0.003)
By year									
2000									
lnINC	-0.013 ***	-0.020 ***	-0.009 ***	-0.060 ***	-0.007	-0.053 ***	-0.013 **	-0.008 ***	-0.005
	(0.002)	(0.006)	(0.002)	(0.013)	(0.007)	(0.014)	(0.005)	(0.003)	(0.006)
RDR/100	0.290 ***	0.017	0.223 ***	-0.039	0.021	-0.060	0.332 ***	0.172 ***	0.160 ***
	(0.008)	(0.016)	(0.011)	(0.044)	(0.015)	(0.042)	(0.033)	(0.011)	(0.030)
OMIGR	0.217 ***	-0.053	0.027	0.048	-0.049	0.097	0.193	0.011	0.182
	(0.035)	(0.044)	(0.038)	(0.120)	(0.043)	(0.115)	(0.127)	(0.035)	(0.118)
CHILDC	0.002	-0.007 ***	-0.002	-0.012 **	-0.006 ***	-0.006	0.000	-0.004 ***	0.004
	(0.002)	(0.002)	(0.001)	(0.005)	(0.002)	(0.004)	(0.004)	(0.001)	(0.003)
2010									
lnINC	-0.026 ***	-0.027 ***	-0.016 ***	-0.065 ***	-0.009	-0.055 ***	-0.016 ***	-0.009 ***	-0.007
	(0.002)	(0.006)	(0.002)	(0.013)	(0.007)	(0.014)	(0.005)	(0.003)	(0.006)
RDR/100	0.178 ***	0.066 ***	0.252 ***	0.061	0.072 ***	-0.012	0.438 ***	0.212 ***	0.226 ***
	(0.008)	(0.016)	(0.012)	(0.047)	(0.015)	(0.043)	(0.036)	(0.011)	(0.032)
OMIGR	0.210 ***	0.260 ***	0.347 ***	0.608 ***	0.237 ***	0.370 ***	0.901 ***	0.276 ***	0.625 ***
	(0.050)	(0.054)	(0.047)	(0.147)	(0.051)	(0.129)	(0.154)	(0.043)	(0.134)
CHILDC	-0.002	-0.001	0.001	-0.003	-0.001	-0.002	0.008 **	-0.001	0.009 ***
	(0.002)	(0.001)	(0.001)	(0.004)	(0.001)	(0.004)	(0.003)	(0.001)	(0.003)

Note : Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 5 Estimation results of children under age 18 in single-mother households

	Non-spatial models						Spatial models			
	Pooled OLS		Fixed effects		Random effects		Fixed effects[a]		Random effects	
	β	std error	β	std error	β	std error	β	std error	β	std error
lnINC	-0.012	0.003 ***	-0.020	0.006 ***	-0.003	0.003	0.003	0.007	0.006	0.004
RDR/100	0.488	0.013 ***	-0.042	0.015 ***	0.214	0.013 ***	-0.006	0.014	0.158	0.013 ***
OMIGR	0.376	0.057 ***	-0.001	0.044	0.049	0.043	0.000	0.040	0.043	0.037
CHILDC	0.004	0.002	-0.007	0.002 ***	-0.004	0.002 ***	-0.005	0.002 ***	-0.007	0.001 ***
Y2010	0.282	0.031 ***	0.179	0.019 ***	0.167	0.021 ***	0.056	0.013 ***	0.041	0.012 ***
lnINC × Y2010	-0.031	0.004 ***	-0.022	0.002 ***	-0.020	0.003 ***	-0.008	0.002 ***	-0.005	0.001 ***
RDR/100 × Y2010	-0.161	0.018 ***	0.114	0.014 ***	0.089	0.015 ***	0.074	0.010 ***	0.057	0.009 ***
OMIGR × Y2010	0.024	0.099	0.354	0.058 ***	0.405	0.061 ***	0.234	0.044 ***	0.240	0.042 ***
CHILDC × Y2010	-0.010	0.003 ***	0.003	0.001 **	0.000	0.001	0.001	0.001	0.001	0.001
Constant	0.098	0.022 ***	0.202	0.052 ***	0.048	0.025 **			0.032	0.019 *
Spatially weighted										
W × lnINC							-0.031	0.009 ***	-0.009	0.004 **
W × RDR/100							-0.063	0.023 ***	-0.087	0.018 ***
W × OMIGR							0.052	0.063	-0.009	0.055
W × CHILDC							-0.001	0.002	0.006	0.002 ***
W × dependent variable							0.675	0.030 ***	0.742	0.015 ***
W × errors							-0.581	0.061 ***	-0.668	0.047 ***
Standard deviation of panel effects			0.020		0.013				0.010	
Standard deviation of errors			0.009		0.009		0.007		0.008	
ρ			0.840		0.699					
Hausman test					1240.12 (p = 0.00)				1057.59 (p = 0.00)	
Wald test of spatial terms							767.07 (p = 0.00)		2968.49 (p = 0.00)	

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Each sample excludes municipalities with null values or no neighboring municipalities. *W* is the binary contiguity matrix. The total number of observations (all) in each sample is 1,801 (3,602). The pooled OLS is weighted by population. [a)] The standard deviation of the panel effects is not presented, since the spatial fixed-effects estimator does not provide consistent estimates for the levels of the panel fixed effects nor for their standard deviation.

Table 6 Average marginal effects for children under age 18 in single-mother households

	Non-spatial models			Spatial models: fixed effects			Spatial models: random effects		
	Pooled OLS	Fixed effects	Rondom effects	Total	Direct	Indirect	Total	Direct	Indirect
2000-2010									
lnINC	-0.027 ***	-0.031 ***	-0.013 ***	-0.100 ***	-0.008	-0.091 ***	-0.023 ***	0.001	-0.024 ***
	(0.002)	(0.006)	(0.003)	(0.017)	(0.006)	(0.017)	(0.009)	(0.004)	(0.009)
RDR/100	0.411 ***	0.015	0.259 ***	-0.098 *	0.022 *	-0.120 **	0.387 ***	0.201 ***	0.186 ***
	(0.009)	(0.014)	(0.012)	(0.059)	(0.013)	(0.055)	(0.052)	(0.012)	(0.048)
OMIGR	0.388 ***	0.176 ***	0.252 ***	0.519 ***	0.145 ***	0.373 **	0.595 ***	0.193 ***	0.402 **
	(0.049)	(0.040)	(0.038)	(0.164)	(0.038)	(0.154)	(0.178)	(0.035)	(0.166)
CHILDC	-0.001	-0.006 ***	-0.005 ***	-0.014 **	-0.005 ***	-0.009 *	-0.004	-0.007 ***	0.003
	(0.002)	(0.001)	(0.001)	(0.006)	(0.001)	(0.006)	(0.005)	(0.001)	(0.005)
By year									
2000									
lnINC	-0.012 ***	-0.020 ***	-0.003	-0.088 ***	-0.004	-0.084 ***	-0.013	0.004	-0.017 *
	(0.003)	(0.006)	(0.003)	(0.018)	(0.007)	(0.018)	(0.009)	(0.004)	(0.009)
RDR/100	0.488 ***	-0.042 ***	0.214 ***	-0.211 ***	-0.020	-0.191 ***	0.276 ***	0.166 ***	0.109 **
	(0.013)	(0.015)	(0.013)	(0.059)	(0.014)	(0.055)	(0.053)	(0.013)	(0.048)
OMIGR	0.376 ***	-0.001	0.049	0.159	0.011	0.148	0.131	0.049	0.082
	(0.057)	(0.044)	(0.043)	(0.160)	(0.040)	(0.149)	(0.177)	(0.038)	(0.164)
CHILDC	0.004	-0.007 ***	-0.004 ***	-0.016 **	-0.006 ***	-0.011 *	-0.005	-0.007 ***	0.002
	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)	(0.006)	(0.006)	(0.001)	(0.005)
2010									
lnINC	-0.044 ***	-0.042 ***	-0.023 ***	-0.111 ***	-0.013 **	-0.099 ***	-0.033 ***	-0.002	-0.031 ***
	(0.003)	(0.006)	(0.003)	(0.017)	(0.006)	(0.017)	(0.009)	(0.004)	(0.009)
RDR/100	0.326 ***	0.072 ***	0.303 ***	0.015	0.064 ***	-0.049	0.497 ***	0.235 ***	0.262 ***
	(0.013)	(0.016)	(0.014)	(0.062)	(0.015)	(0.057)	(0.057)	(0.014)	(0.051)
OMIGR	0.401 ***	0.353 ***	0.454 ***	0.878 ***	0.280 ***	0.599 ***	1.060 ***	0.337 ***	0.722 ***
	(0.081)	(0.054)	(0.054)	(0.195)	(0.049)	(0.171)	(0.214)	(0.047)	(0.187)
CHILDC	-0.006 **	-0.004 ***	-0.005 ***	-0.012 **	-0.004 ***	-0.008	-0.003	-0.006 ***	0.004
	(0.002)	(0.001)	(0.001)	(0.006)	(0.001)	(0.006)	(0.005)	(0.001)	(0.005)

Note : Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A1 Average marginal effects for children under ages 6 and 18 in single-mother households: spatial fixed-effects models

	Children under age 6			Children under age 18		
	Total	Direct	Indirect	Total	Direct	Indirect
2000-2010						
lnINC	-0.553 **	-0.010	-0.544 **	-0.772 ***	-0.010	-0.761 ***
	(0.252)	(0.007)	(0.253)	(0.272)	(0.006)	(0.272)
RDR/100	-0.874	0.047 ***	-0.921	-1.056	0.021	-1.076
	(0.668)	(0.014)	(0.667)	(0.775)	(0.013)	(0.773)
OMIGR	3.765	0.081 **	3.683	3.216	0.131 ***	3.085
	(2.323)	(0.040)	(2.321)	(2.047)	(0.037)	(2.040)
CHILDC	-0.033	-0.004 **	-0.030	0.033	-0.003 **	0.036
	(0.057)	(0.001)	(0.057)	(0.091)	(0.001)	(0.090)
By year						
2000						
lnINC	-0.551 **	-0.008	-0.542 **	-0.755 ***	-0.002	-0.753 ***
	(0.252)	(0.007)	(0.252)	(0.268)	(0.007)	(0.267)
RDR/100	-0.923	0.021	-0.944	-1.157	-0.032 **	-1.125
	(0.683)	(0.0157)	(0.683)	(0.794)	(0.015)	(0.792)
OMIGR	3.519	-0.049	3.567	3.090	0.066	3.024
	(2.224)	(0.044)	(2.223)	(2.017)	(0.042)	(2.012)
CHILDC	-0.039	-0.007 ***	-0.032	0.032	-0.004 **	0.036
	(0.057)	(0.002)	(0.057)	(0.091)	(0.002)	(0.090)
2010						
lnINC	-0.556 **	-0.011 *	-0.545 **	-0.788 ***	-0.019 ***	-0.769 ***
	(0.253)	(0.007)	(0.253)	(0.277)	(0.006)	(0.277)
RDR/100	-0.825	0.072 ***	-0.898	-0.954	0.073 ***	-1.027
	(0.654)	(0.016)	(0.652)	(0.759)	(0.015)	(0.755)
OMIGR	4.011 *	0.211 ***	3.800	3.342	0.196 ***	3.146
	(2.426)	(0.054)	(2.422)	(2.079)	(0.052)	(2.069)
CHILDC	-0.028	-0.001	-0.027	0.034	-0.003 **	0.037
	(0.057)	(0.001)	(0.057)	(0.091)	(0.001)	(0.091)

Note: Standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.